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Robots and reshoring: Evidence from Mexican local labor markets*

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Abstract

Robots in advanced economies have the potential to reduce employment in offshoring countries by fueling reshoring. Using robots instead of humans for production may reduce the relative cost of domestic production and, in turn, lower demand for imports from offshoring countries. I analyze the impact of robots on employment in an offshoring country, using data from Mexican local labor markets between 1990 and 2015. A recent literature shows that the effect of robots on local employment can be estimated by regressing the change in employment on *exposure to domestic robots* in local labor markets. I similarly construct a measure of *exposure to foreign robots*, assuming that the share of US robots competing with Mexican labor is proportional to that industry's initial reliance on Mexican imports. Using robot penetration in the rest of the world (i.e., neither in Mexico nor in the US) as an instrument for domestic and foreign robotization, I show that the use of robots in the US has a robust and sizable, negative impact on employment in Mexico by reducing exports to the US. The effect is not driven by pre-existing trends, the automotive industry or migration patterns. It is strongest for low-skilled machine operators and technicians in highly robotized manufacturing industries as well as high-skilled managers and professionals in the service industry.

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1 Introduction

The debate about the impact of robots on employment focuses on advanced economies, although offshoring countries are likely to be more affected: Robots substitute for low-skilled labor (Graetz and Michaels, 2015). In the past few decades, many low-skill, blue-collar tasks have been moved from rich to offshoring countries (e.g., China, Mexico, India, Bangladesh, Vietnam), leaving workers in those countries especially exposed to robots (cf. Autor et al., 2015). Moreover, there is growing anecdotal evidence for so-called 'reshoring', which is fuelled by advances in robot capabilities in developed countries and likely to reduce employment in offshoring countries.[1] Increased use of robots in the developed world may thus have an especially large impact on employment in offshoring countries.

Economists have recently started to examine the impact of *industrial robots* on employment, but only for *developed* countries. Graetz and Michaels (2015) are the first to examine their effect on several economic variables across 17 highly developed countries and industries.[2] They find that increases in robot density have increased labor productivity, and that there is some evidence that it reduced the hours of low-skilled workers. Just recently, Acemoglu and Restrepo (2017) added to this discussion by examining, both theoretically and empirically, the effect of robots on employment and wages in the United States. First, they develop a theoretical model in which robots compete against human labor in specific tasks. They show that in general equilibrium, the effect of robots can be estimated by a relatively simple regression (cf. Section 2). Second, exploiting variation in exposure to robots across US local labor markets, they find that one new robot reduces employment by six workers in the United States. Finally, Dauth et al. (2017) conduct a similar analysis for Germany, and find no effect of robots on overall employment, but negative effects on earnings of low- and middle-skilled workers.

In spite of these findings, it remains relevant to answer the same question for offshoring countries. Robots may affect those countries distinctly via a recent phenomenon called *reshoring*. Reshoring describes the reverse process of offshoring, where manufacturing is moved to another country where labor is cheaper. One of the reasons why companies decide to reshore production is that advances in robotic automation technologies reduce their costs of production, no matter where they produce. This, in turn, increases the relative attractiveness of domestic production as compared to offshoring. Robots are thus likely to fuel reshoring.

Recent examples for this reshoring process are the new proto-type "Speedfactories" of German sportswear company Adidas located in Ansbach, Germany and Atlanta, US, which produce 500,000 pairs of shoes per year using mainly industrial robots. Traditionally, companies in this industry had offshored production to cheap labor locations like China, Vietnam and Indonesia. Since robots cannot perform all tasks, the Speedfactories employ about 160 people

[1] cf. Economist (2013), Economist (2017), Lewis (2014)

[2] All 17 countries are in top-30 in terms of GDP per capita (excl. oil countries and very small tax haven countries such as Qatar, UAE and Puerto Rico, Bahamas, respectively.)

locally in Ansbach and Atlanta, compared with more than a thousand in a typical factory in an offshoring location (cf. Economist, 2017).

In this paper, I estimate the effect of both *domestic* and *foreign* robots on employment in offshoring countries, using 1990–2015 data from Mexican local labor markets as well as robot shipment data for Mexico, the US and 19 other countries. Similar to Acemoglu and Restrepo (2017), I use a local labor market's exposure to robots to estimate the effect of *Mexican* robots on local employment. In addition, I also consider an exports-producing sector, which may be affected by *US* robots. The effect of US robots on employment in a local labor market is identified via a similar measure, utilizing the US national penetration of robots into each industry, the local distribution of employment across industries, and the initial reliance of the US on imports from Mexico. I use increased robot usage in the rest of the world (neither US nor Mexico) as an instrument for Mexican and US robotization to purge the results from endogeneity concerns resulting from an industry's or specialized local labor market's decision to adopt robots.

The IV results suggest that US robots have a negative impact on employment in Mexico by reducing exports to the US. I explore alternative explanations such as pre-existing trends, the automotive industry or migration across local labor markets driving the results, and find no support for these. Two groups of workers seem to be most affected by US robots: First, low-educated machine operators and technicians in manufacturing, and second, highly-educated service workers in managerial and professional occupations. The estimates imply that a local labor market with an average exposure to US robots experienced a 2.9 percentage points lower growth in the employment-to-population ratio, compared with no such exposure. At the national level, this amounts to about 1.7 million fewer jobs in Mexico. This implies that one US robot substitutes for roughly 11 Mexican workers. The majority of this employment effect is mirrored in reduced export volumes to the US and fewer Maquiladora factories – dedicated export-manufacturing plants in Mexico.

The remainder of this paper is stuctured as follows: Section 2 presents a model, in which robots compete with human labor in different tasks. This is helpful to understand the forces at work and serves as a motivation for the empirical strategy. I extend the basic model by an exports-producing sector to identify the effect of foreign robot stocks. Section 3 lays out the empirical strategy. Section 4 describes the construction of the data set. Section 5 presents the empirical results, including several robustness checks, a subgroup-analysis, and explores the mechanism behind the results. Section 6 concludes.

2 The impact of robots on employment in theory

In this section, I extend the model developed by Acemoglu and Restrepo (2017) with an exports-producing sector to not only identify the effect of *domestic*, but also *foreign* robots on local employment.

2.1 Domestic robots

In this model, robots compete against human labor in the production of different tasks. In general equilibrium, robots may increase or reduce employment and wages, depending on the relative size of countervailing effects. Using this model, the local labor market effects of robots can be estimated by regressing the change in employment and wages on the *exposure to robots* in each local labor market, which is defined from the national penetration of robots into each industry and the local distribution of employment across industries.

Each commuting zone (CZ) c maximizes aggregate consumption (from several industry-specific products), taking into account its relative tastes α_i for each industry-product, given by

$$Y_c = \left(\sum_{i \in I} \alpha_i Y_{ci}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where σ>0 denotes the elasticity of substition across goods produced in different industries.

Production of a CZ's industry-good X_{ci} takes place by combining a set of tasks $s \in [0, S]$ in fixed proportions so that

$$X_{ci} = A_{ci} \min_{s \in [0,S]} \{x_{ci}(s)\}, \tag{2}$$

where A_{ci} is the productivity of CZ c in industry i and $x_{ci}(s)$ is the quantity of task s utilized in the production of X_{ci}. Differences in A_{ci} and α_i thus give rise to different industry compositions across CZs.

Robots are modeled by assuming that each industry-product requires a set of tasks in fixed proportions, of which a subset $[0, M_i]$ is technologically automated, such that it can be produced by both humans and robots. More formally,

$$x_{ci}(s) = \begin{cases} \gamma l_{ci}(s) & \text{if } s > M_i, \\ \gamma l_{ci}(s) + r_{ci}(s) & \text{if } s \leq M_i \end{cases} \tag{3}$$

where $l_{ci}(s)$ and $r_{ci}(s)$ denote labor and robots used in the production of tasks s in CZ c and industry i, respectively. The productivity of robots is normalizd to one, such that $\gamma > 0$ denotes the relative productivity of labor. Robotization takes the form of an increase in M_i (dM_i), i.e., an increase in the number of tasks in which robots can substitute for labor. Crucially, more conventional technologies (such as traditional ICT) can be modeled by increasing γ, thus complementing labor.

Finally, supply of labor L_c and robots R_c in each CZ are defined as

$$W_c = \mathcal{W}_c Y_c L_c^{\epsilon}, \quad \text{with } \epsilon \geq 0; \text{ and} \tag{4}$$

$$Q_c = \mathcal{Q}_c \left(\frac{R_c}{Y_c}\right)^{\eta}, \text{ with } \eta \geq 0 \tag{5}$$

where Q_c is the price of robots, and W_c is the wage rate in commuting zone c. These specifications imply that $1/\epsilon$ is the Frisch elasticity of labor supply, while $1/\eta$ is the elasticity of the supply of robots.

Examining the equilibrium change in labor demand (L_c^d) in response to automation under autarky is helpful to understand the three different forces at work in this model:[3]

$$d \ln L_c^d = \underbrace{-\sum_{i \in I} \ell_{ci} \frac{dM_i}{1 - M_i}}_{\text{displacement effect}} \underbrace{-\sigma \sum_{i \in I} \ell_{ci} d \ln P_{X_{ci}}(M_i)}_{\text{price-productivity effect}} \underbrace{+ d \ln Y_c(M_i)}_{\text{scale-productivity effect}}, \tag{6}$$

where ℓ_{ci} denotes industry i's share of total employment in CZ c, $P_{X_{ci}}$ denotes the price for industry-product X_i in CZ c, and Y_c denotes CZ c's total output.

There are opposing effects on labor demand in this equation: On the one hand, the first term describes the (negative) *displacement effect*, i.e., the direct effect of robots substituting for human labor, holding prices and output constant. On the other hand, there are two opposing (positve) indirect effects: (i) the *price-productivity effect* resulting from lower prices due to higher robot usage, allowing the *industry* to expand and increase its demand for labor, and (ii) the *scale-productivity effect*, resulting from lower prices in the aggregate, allowing the *total CZ* to expand and demand more labor. Hence, in principle, robotization could lead to either a reduction or an increase in labor demand in this model. This depends on whether the negative displacement effect or the positive productivity effects are larger.

Equation (6) is in terms of robotic automation *technology* M_i, not the number of robots R_i. Using the facts that $1/\gamma$ is the productivity of robots relative to humans, the term $\frac{dM_i}{1-M_i} \approx \frac{1}{\gamma}\frac{dR_i}{L_i}$ when $M_i \approx 0$. This is more convenient for the empirical analysis.

Finally, the full model allows for trade across CZs, resulting in a more involved general equilibrium equation that can be simplified to the following:

$$d \ln L_c = \beta_c \sum_{i \in I} l_{ci} \frac{dR_i}{L_i} + \epsilon_c, \text{ with} \tag{7}$$

$$\beta_c = \left(\frac{1+\eta}{1+\varepsilon}\big(s_c\lambda + (1-s_c)\sigma\big)\pi_c - \frac{1+\eta}{1+\varepsilon}\frac{s_c\lambda + 1 - s_c}{s_c}\right)\frac{(1+\varepsilon)s_c\gamma}{(1+\varepsilon)s_c\lambda + (1+\eta)(1-s_c)},$$

[3] See Acemoglu and Restrepo (2017) for proofs of existence and uniqueness of all equilibria presented in

where s_c is the labor share in CZ c, λ is the elasticity of substitution between varieties sourced from different CZs, and $\pi_c = 1 - \frac{Q_c \gamma}{W_c}$ are the cost-saving gains from using robots instead of labor. dR_i is the increase in the number of robots in industry i, and thus $\sum_{i \in I} \ell_{ci} \frac{dR_i}{L_i}$ corresponds to a CZ's *exposure to robots*.[4]

2.2 Foreign robots

In a world without trade *across* countries it would be sufficient to estimate the effect of robots on local employment using the above equation and data on robot installations and initial employment in Mexico. However, employment in offshoring countries stems to a large extent from exports.[5] Workers in the exports-producing sector thus do not only compete with domestic, but also foreign robots.[6]

To identify the effect of foreign robots on domestic employment, I extend the model above with an exports-producing sector. I consider only two countries: a small home country (Mexico) and a large foreign country (United States). This is a parsimonious extension of the model including trade across CZs, treating the foreign country as an additional (large) CZ. I assume that of all the tasks $s \in S$ necessary to produce final output in industry i, an initial share F_i is cheaper to produce with Mexican than US labor. This creates an exports-producing sector in Mexico. I further assume that these tasks are uniformly distributed on the continuum of tasks, ranked by ease of automation (cf. Figure 1).[7] Hence, in a world with no robots initially ($M_i = 0$), all tasks $s \in F_i$ are performed using Mexican labor. With robots ($M_i > 0$), however, only non-automated tasks that were initially profitable to import from Mexico ($s > M_i$ and $s \in F_i$) are produced using Mexican labor.

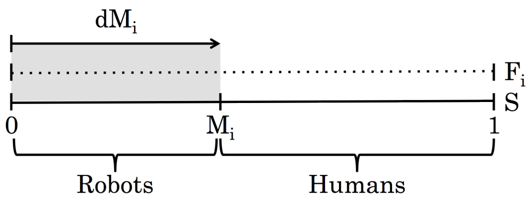


Figure 1: Relationship between share of industry-tasks S profitable to import from Mexico (F_i) and technologically automatable (M_i)

this subsection.

[4]In an updated version of Acemoglu and Restrepo (2017), the result of a slightly adjusted model includes an "adjustment term", which captures that without innovation in robot capabilities, an industry's robot stock will rise proporional to its initial robot density simply as a result of industry growth. The authors find that this adjustment term is not quantitatively important, as most industries feature either low initial robot density or only moderate growth rates. I therefore decided to use this simpler version of their result.

[5]In 2015, Mexican exports to the United States made up roughly 30% of total Mexican GDP.

[6]In particular, assuming that the productivity and costs of robots are the same no matter where they operate, and that tasks are perfectly seperable, it is never optimal for importing firms to employ robots abroad. They can always save transportation costs by employing them at home. In this extreme case, exports-producing workers compete *only* with foreign robots.

[7]This essentially assumes that the share of each industry's foreign robots competing with labor in the home country is proportional to the foreign industry's initial reliance on imports from the home country. This also implies that only robots in industries with tradable goods compete with labor at home. If, for some reason, some industry's robots are a much closer substitute to foreign labor than another industry's, this assumption may be violated.

Assuming workers in both countries have the same productivity, initial industry i employment in the exports-producing sector is thus given by $L_i^f F_i$, i.e., a fraction of all workers producing output for foreign consumption (L_i^f). As now the foreign country needs to be included as an additional commuting zone, equation (7) becomes

$$d \ln L_c = \beta_c \sum_{i \in I} \ell_{ci} \frac{dR_i^d + dR_i^f}{L_i^d + L_i^f} + \epsilon_c, \tag{8}$$

where dR_i^d and dR_i^f are the change in the number of robots in the domestic (Mexico) and foreign country (US), and L_i^d and L_i^f are the numbers of workers producing output for domestic and foreign consumption, respectively. Given that dM_i takes the same form in both countries, F_i is uniformly distributed across S, and initially in both countries only labor is used for production, each industry's increase in number of robots per worker is the same in the foreign- and domestic-goods-producing sectors in both countries. Hence, Equation (8) can be rewritten in terms of employment in Mexico:

$$d \ln L_c = \beta_c \sum_{i \in I} \ell_{ci} \frac{dR_i^d + dR_i^f F_i}{L_i^d + L_i^f F_i} + \epsilon_c \tag{9}$$

$$\Leftrightarrow \quad d \ln L_c = \beta_c \sum_{i \in I} \ell_{ci} \frac{dR_i^d + dR_i^f F_i}{L_i} + \epsilon_c \tag{10}$$

$$\Leftrightarrow \quad d \ln L_c = \beta_c \sum_{i \in I} \ell_{ci} \frac{dR_i^d}{L_i} + \beta_c \sum_{i \in I} \ell_{ci} \frac{dR_i^f}{L_i} F_i + \epsilon_c, \tag{11}$$

where L_i is the home country's industry employment. Hence, what matters in theory for changes in local employment in the home country are each local labor market's *exposures* to domestic and foreign robots ($\sum_{i \in I} \ell_{ci} \frac{dR_i^d}{L_i}$ and $\sum_{i \in I} \ell_{ci} \frac{dR_i^f}{L_i} F_i$, respectively). The latter is a function of the local distribution of employment across industries ($\sum_{i \in I} \ell_{ci}$) and the penetration of *foreign* robots per domestic worker into each industry (dR_i^f / L_i) scaled by the foreign country's initial reliance on imports from the home country in industry i (F_i).

3 Empirical strategy

Equation (11) can be taken to the data directly to measure the effect of domestic and foreign robots on local employment in Mexico. The resulting exposure to domestic robots variable may, however, suffer from measurement error and endogeneity. First, there may be some measurement error due to the non-observed robot data for some of the years. This would cause OLS to underestimate the true effect. Second, it may be endogenous for two reasons: Contemporaneous shocks to certain *industries* or to certain *local labor markets* highly specialized in a certain industry may have had distinct effects on their robot and labor demand. A likely candidate for such a shock is Mexico's entry into the North American Free Trade Agreement (NAFTA) in 1994. NAFTA may have put upward pressure on specifically those industries or specialized local labor markets that already had the highest employment-to-population ratios and thus less room for expansion. Such industries or local labor markets may have then decided to employ the most robots. This would result in lower employment growth in those local labor markets with highest robot growth, but the causality would be reverse. In that case, OLS would overestimate the true effect.

I apply an IV strategy to address both issues. In particular, I use the contemporaneous increase in robot density in the rest of the world as an instrument for the increase in Mexico's robot density, and call the resulting measure *exogenous exposure to domestic robots*:

$$\begin{array}{c}\text{exogenous}\\ \text{exposure to}\\ \text{domestic robots}_{c,t}\end{array} \equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{robots^{WLD}_{i,'15} - robots^{WLD}_{i,'93}}{L^{WLD}_{i,'95}} \right),$$

where the superscript *WLD* indicates the sum over all countries in the robot data except for the US and Mexico.[8] I will henceforth refer to this group of countries as the "rest of the world".

Similarly, the introduction of NAFTA may lead to endogeneity of the exposure to foreign robots variable, too. In particular, when deciding about the employment of robots, US firms may have taken into account local labor market conditions in Mexico more strongly after the free trade agreement. For example, if Mexican local labor markets specialized in automotive manufacturing had relatively low employment-to-population ratios, and thus more room to expand, US automotive firms would have had lower incentives to employ robots at home, and vice versa. Any such scenario would cause the OLS estimates to be biased.

To account for this, I substitute the increase in *US* robots by industry with the increase in rest-of-the-world robots by industry, and use the resulting *exogenous exposure to foreign robots* measure as an instrument:

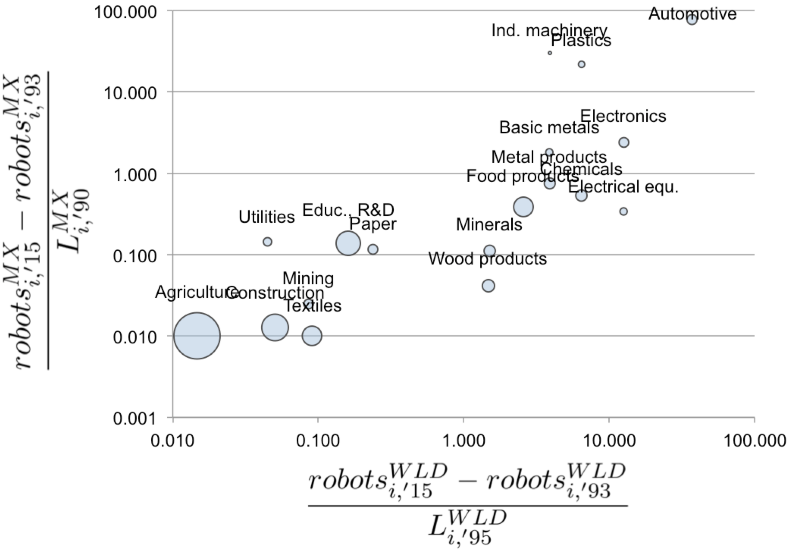
$$\begin{array}{c}\text{exogenous}\\ \text{exposure to}\\ \text{foreign robots}_{c,t}\end{array} \equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{robots^{WLD}_{i,'15} - robots^{WLD}_{i,'93}}{L_{i,t}} \right) F^{US}_{i,'92},$$

where $F^{US}_{i,t} = \frac{I_{i,t}}{Y_{i,t}}$ denotes the share of Mexican imports I of total output Y in industry i in the US in year t.[9]

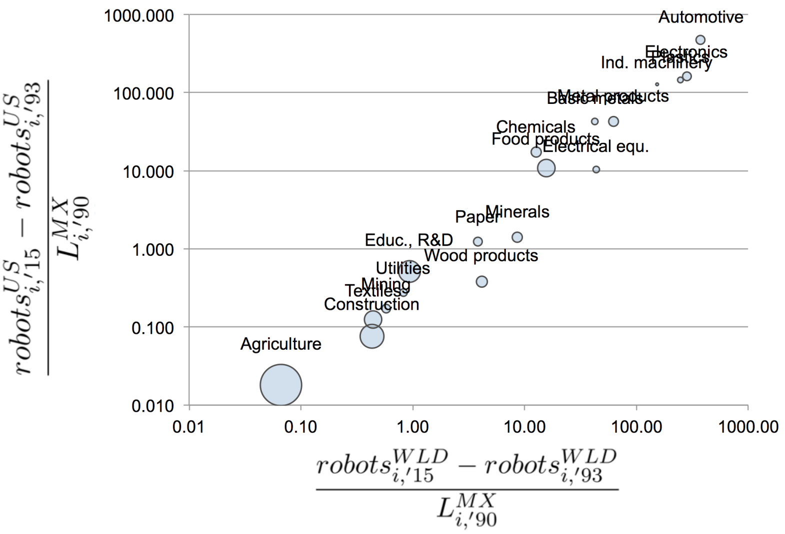
The main idea behind these two instruments for the exposure to domestic and foreign robots is that robot adoption in the rest of the world has a better chance of being unrelated to local labor market conditions in Mexico. In particular, these instrumental variables are likely to be unaffected by NAFTA, the most obvious cause for concern. Moreover, using the long-

[8] In particular, the IFR robot data includes Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Hungary, Italy, Japan, South Korea, Netherlands, Poland, Portugal, Romania, Sweden, Slovakia and the United Kingdom. Data on employment by industry L_i^{WLD} is from 1995, as this is the earliest year for which industry-level employment data exists for all those 19 countries.

[9] UN Comtrade database only contains such data from 1992 onwards, so the 1992 values are used as an approximation for the 1990 values.



A. First-stage for exposure to domestic robots



B. First-stage for exposure to foreign robots

Note: Panel A presents industry-level variation between robot densification in Mexico and the rest of the world, which is defined as all countries in the sample, except for Mexico and the US. Panel B presents the corresponding relationship between the increase in US and rest-of-the-world robots per Mexican worker. Bubble size indicates Mexican industry employment in 1990. Hence, the variables on the vertical and horizontal axes of Panels A and B are used in the construction of the endogenous and exogenous exposures to *domestic* and *foreign* robots, respectively.

Figure 2: Industry-level relationship between endogenous exposure to robots variables and instruments

difference (1993–2015) industry-variation also in the short-difference specifications is more robust against contemporaneous shocks affecting both robot adoption and employment in the same time period. These are relevant instruments, if quality improvements and price reductions, which affect industries across countries similarly, drive the adoption of robots. The first-stage relationship of the industry-variation for both measures is presented in Figure

2. Note that the initial employment shares l_{ci} and import reliance F_i are not instrumented for. The instrument validity thus rests on the assumption that these initial shares are exogenous. I provide support for this assumption in the discussion of the main results.

The identifying variation in these two instruments arises from two sources: First, F_i, a US industry's share of Mexican imports of total output, is included only in the instrument for foreign robots. Thus not only an industry's increase in robot density matters for a Mexican local labor market's exposure to foreign robots, but also whether that industry in the US was initially highly reliant on Mexico. Second, the denominator is L_i^{WLD} for the domestic robots instrument and L_i^{MX} for the foreign robots instrument. The goal for the foreign robots instrument is to measure the degree of robotic automation in the most important destination market per worker in the *origin* market (as in the endogenous variable, US robots over Mexican workers) without using the potentially endogenous number of US robots. The number of robots in the rest of the world has a better chance of being exogenous to Mexican local labor market conditions than that in the US. It is, however, not straightforward for which origin markets the country group making up the rest of the world is the most important destination market. Therefore I stick to Mexican industry employment in the denominator. While using the number of robots in the rest of the world should eliminate potential endogenity of US robots, it is reassuring that the US distribution of robots across industries is in fact very similar to that in the rest of the world, as evident in Panel B of Figure 2.

The key estimating equation to identify and quantify the effect of robots on local employment in Mexico between t and $t+1$ thus becomes:

$$\Delta_{t:t+1} \begin{array}{c}\text{employment-to-}\\ \text{population}\\ \text{ratio}_c\end{array} = \alpha + \beta^d \begin{array}{c}\text{exposure}\\ \text{to domestic}\\ \text{robots}_{c,t:t+1}\end{array} + \beta^f \begin{array}{c}\text{exposure}\\ \text{to foreign}\\ \text{robots}_{c,t:t+1}\end{array} + \gamma X_c + \epsilon_c, \tag{12}$$

using the two *exogenous exposure to robots*$_{c,t}$ variables as instruments, and clustering standard errors by state.

4 Data

To estimate equation (12), I first construct CZs as the unit of observation and then the key variables as described in this subsection. Summary statistics of all relevant variables are presented in Table A1 in the Appendix.

4.1 Commuting zones

Using local labor markets as a unit of observation is motivated by the mounting evidence that labor, and especially the low-skilled, is not perfectly mobile across space.[10] There are several potential definitions of local labor markets (counties, states, metropolitan areas). However, most of them have drawbacks: some represent political boundaries that do not

[10] Autor and Dorn (2013), Autor et al. (2013), Blanchard et al. (1992), Glaeser and Gyourko (2005), Malamud and Wozniak (2012)

necessarily coincide with economic boundaries (states, counties), others only cover urban areas (metropolitan areas).

Following a recent literature, I thus use *commuting zones* (CZs) as the unit of observation.[11] CZs are clusters of municipalities that feature strong commuting ties within, and weak commuting ties across CZs. Such clusters are constructed in three steps: In a first step, all municipalities within a *Zona Metropolitana* are clustered into one large municipality. In a second step, the intensity of commuting from any municipality i to j (S_{ij}) is computed by adding up the number of people commuting from i to j, and dividing them by the number of residents in i. In a third step, municipalities are clustered together, if more than 10% of residents of either municipality commutes into the other. This results in 1,806 CZs (from 2,438 municipalities) and a defintion of local labor markets that is robust to the criticism of most alternative definitions: Unlike states or counties, it features economically relevant boundaries and, unlike metropolitan areas, it includes rural regions.

4.2 Change in employment

The Instituto Nacional de Estadística, Geografía e Informática (INEGI) in Mexico conducted its first census at the municipality level in 1960. Since then, it repeated such a census every ten years. Similar to other censuses, they contain a large number of variables for each individual, including employment status, wages, municipality of residence, municipality of work place, and education level. Data samples of about 1% of the population for 1960 and 1970, and 10% of the population for all the remaining censuses are available via IPUMS International (IPUMS).

Given the cross-walk from municipalities to CZs, the census data can be aggregated by CZ to construct the main dependent variable:

$$\Delta_{t:t+1} \begin{array}{c}\text{employment-to-}\\ \text{population}\\ \text{ratio}_c\end{array} = \frac{L_{c,t+1}}{N_{c,t+1}} - \frac{L_{c,t}}{N_{c,t}},$$

where $L_{c,t}$ is private employment (excl. self-employed and public sector employment) and $N_{c,t}$ is the working-age population in commuting zone c and year t. The dependent employment variables and several control variables are constructed using census data from 1970, 1990, 2000 and 2015.

4.3 Exposure to domestic robots

The two main explanatory variables of interest – *exposure to domestic robots* and *exposure foreign robots* – are constructed combining census and trade data with robot data from the International Federation of Robotics (IFR). The IFR collects data on shipments and operational stocks of *industrial robots* by country and industry since 1993 "based on consolidated data provided by nearly all industrial robot suppliers world-wide" (IFR, 2014, p.25). Industrial robots are defined as "automatically controlled, reprogrammable, multipurpose manipula-

[11] Atkin (2016), Autor et al. (2015) and Acemoglu and Restrepo (2017), among others

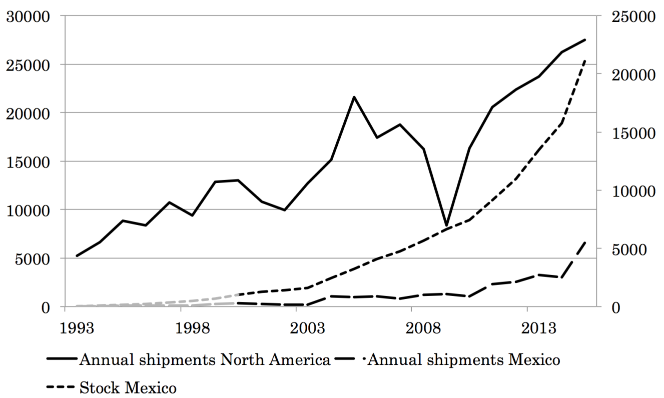
tor[s] programmable in three or more axes, which can be either fixed in place or mobile for use in 13 industrial automation applications” (IFR, 2014, p.29).

Typical applications of industrial robots are pressing, welding, packaging, assembling, painting and sealing, all of which are common in manufacturing industries; as well as harvesting and inspecting of equipment, which are prevalent in agriculture and the utilities industry, respectively (IFR, 2014, p.31-38).

Ideally, I would use data on robot installations per CZ directly to measure increases in robot density. However, robot data on such a granular geographical level does not exist. Instead, and in line with the theory presented before, I construct a Bartik-style estimate based on the number of robots per industry and the distribution of employment across industries and CZs. I will refer to this as *exposure to domestic robots*:[12]

$$\begin{array}{c}\text{exposure}\\ \text{to domestic}\\ \text{robots}_{c,t:t+1}\end{array} \equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{robots_{i,t+1} - robots_{i,t}}{L_{i,t}} \right), \tag{13}$$

where $\ell_{ci,t} = L_{ci,t}/L_{c,t}$ denotes industry i’s share of total employment in CZ c in year t, and $robots_{i,t}$ is the stock of robots per industry i in year t. Using only the distribution of employment across CZs in the beginning of the period (and not in $t+1$) is useful to avoid any mechanical correlation with the dependent variable. This measure is referred to as *exposure to* domestic robots, since variation is driven by CZs’ initial conditions rather than actual robot installations.



Note: The solid line shows the reported figures for annual shipments of robots to North America (left axis). The long dashed line shows the corresponding values for Mexico (right axis). Based on this, Mexico’s share of annual robot shipments to North America can be calculated for 2000-2015. An exponential function is then fitted through the reported shares in order to extrapolate the shares for 1993-1999. Multiplying those with the corresponding annual values of the solid line yields extrapolated annual shipments of robots to Mexico from 1993–1999. Summing up these annual shipments, and assuming an average lifetime of twelve years per robot, results in the extrapolated robot stock for Mexico (dotted line, right axis).

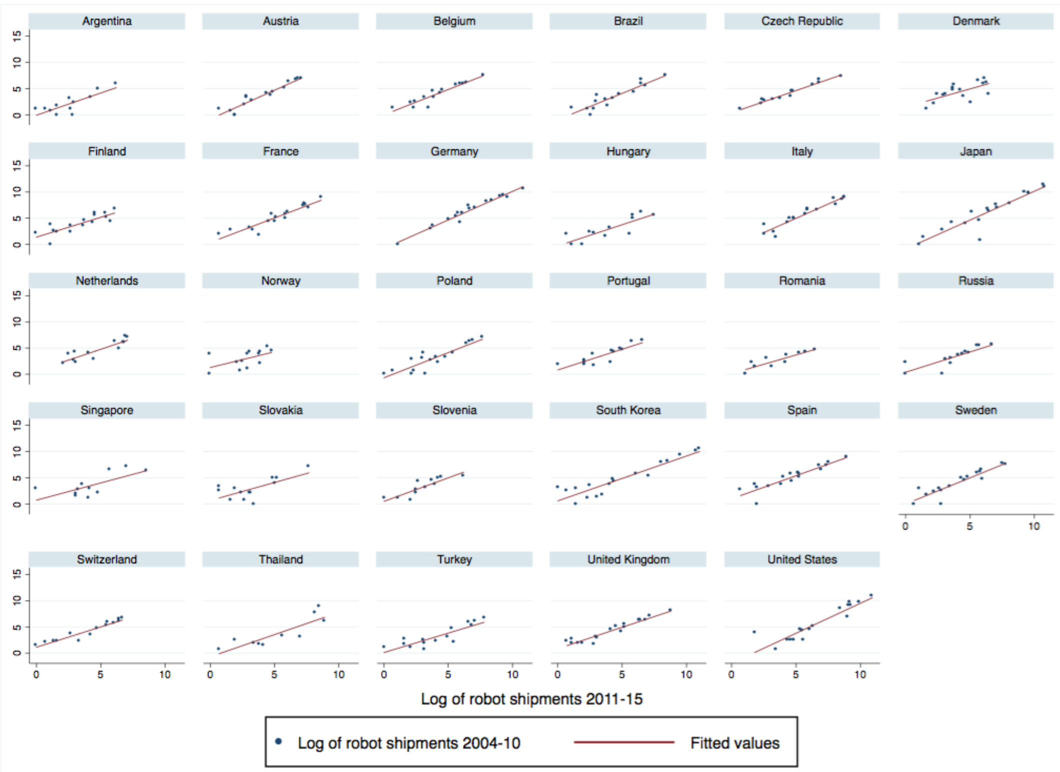
SOURCE: IFR World Robotics Database

Figure 3: Reported annual robot shipments to North America (solid) and extrapolated robot stock in Mexico (long dashed), 1993–2015

[12]Analogous to "US exposure to robots" in Acemoglu and Restrepo (2017).

This is a good approximation of the actual number of robots employed in each CZ, if each industry's robots are distributed across CZs proportional to the industry's initial share of employees in each CZ. For example, if 10% of the Mexican automotive industry's employment had been located in Saltillo in 1990, it is assumed that subsequently 10% of the automobile industry's robots have been installed in Saltillo. Acemoglu and Restrepo (2017) present some empirical evidence for the US that this is a sensible assumption. Their analogous robot exposure measure shows a strong association with both the presence and number of robot integrators in US commuting zones (cf. Figure 6 and Table A6 in their paper).

To estimate the long-difference specification, i.e., changes between 1990 and 2015, the initial number of robots per industry in 1990 is required. Unfortunately, data on robot stocks in Mexico are not available for 1990. However, it seems reasonable to assume that the stock of robots was close to zero, given that (i) annual shipments of robots to North America were still relatively low in the beginning of the 1990's and (ii) Mexico's share of North American annual shipments only began its sharp rise in the late 2000's (cf. Figure 3). I therefore assume that the number of robots per industry in Mexico was zero in 1990.



SOURCE: IFR World Robotics Database

Figure 4: Relationship between industries' robot shipments 2011–2015 and 2004–2010

Moreover, the IFR only started reporting Mexican robot shipments *by industry* in 2011. As they calculate their robot stock values by simply adding up robot shipments over the last 12 years, the shipments between 2004 and 2010 are missing in the reported robot stock values for

2015. Fortunately, there exist data by industry for 2011–2015, which may be used to estimate the missing 2004–2010 values, exploiting existing data from other countries. For this to be a plausible estimate, the relationship between 2011–2015 and 2004–2010 shipments per industry must be strong and consistent across countries. This can be checked for empirically, using data from 29 other countries, for which industry-level data exists from 2004 onwards.

Figure 4 provides visual evidence about the relationship between robot shipments from 2011–2015 and their corresponding values from 2004–2010 by industry for all such 29 countries. Running a random-effects regression of log shipments from 2011 to 2015 on log shipments from 2004 to 2010 for the sample of 29 countries, and clustering the standard errors by country, yields:

$$\ln(\widehat{\text{Shipments } 2004-10})_{ij} = \underset{(0.024)}{0.929} \cdot \ln(\text{Shipments } 2011-15)_{ij} + \hat{\gamma} X_{ij},$$

where $n = 493$ and $R^2 = 0.84$, i and j denote industry and country, respectively, and X_{ij} is a vector of covariates incl. a constant.[13] Assuming Mexico is not systematically different from the average of the 29 countries in the sample, I therefore use the observed industry variation between 2011 and 2015 and impose it on the aggregate values between 2004 and 2010.

4.4 Exposure to foreign robots

Finally, in light of the large share of exports-producing employment in Mexico and the emergence of reshoring, it seems relevant to include the exposure to *foreign* robots. Motivated by the theory presented before and in particular Equation (11), I construct a measure of exposure to *foreign* robots per CZ as:

$$\begin{matrix}\text{exposure} \\ \text{to foreign} \\ \text{robots}_{c,t:t+1}\end{matrix} \equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{robots^{US}_{i,t+1} - robots^{US}_{i,t}}{L_{i,t}} \right) F^{US}_{i,t} \tag{14}$$

Note that I only use US robots, as exports to the US represent the majority, or about 80% of overall Mexican exports between 1990 and 2015. A CZ's exposure to foreign robots is thus high, if it was highly specialized in industries where (a) US industries have employed many robots per Mexican worker and (b) US output relied heavily on Mexican imports intially.

4.5 Computers and Chinese import competition

A contemporaneous shock that might affect the results is the replacement of routine jobs by computers (computerization). Data on routine task intensity does not exist on the occupation classification level used in Mexican censuses. As a workaround, I use occupation-level data on routine task intensity in the US from Autor and Dorn (2013). As the occupation classifications used in the US and Mexican census vary from one another, I first aggregate occupations to common occupation groups. In a second step, I use the arithmetic means of routine task

[13] Covariates include baseline values of GDP per capita and population size, as well as continent dummies.

intensity across the various occupations within an occupation group.[14]

Another relevant contemporaneous shock that I control for is the increase in import competition from China both at home and abroad. I use data on trade flows – most importantly Chinese imports to Mexico and the US – from the UN Comtrade Database. Starting in 1992, this database contains data on trade flows from China to Mexico and the US by 6-digit HS industry classification. The control variable *exposure to Chinese import competition* takes into account changes in Chinese imports to Mexico as well as the United States, discounting the latter by the initial reliance of US industries on Mexican imports. It accounts for the fact that an exports-oriented country not only competes with Chinese imports at home, but also in foreign markets. It is constructed as a Bartik-style measure equivalent to the *domestic plus international exposure to Chinese imports* in Autor et al. (2013), namely:

$$\begin{array}{c}\text{exposure to}\\ \text{Chinese import}\\ \text{competition}_{c,t:t+1}\end{array} \equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{\left(imp_{i,t+1}^{CNMX} - imp_{i,t}^{CNMX}\right) + F_{i,t}^{US}\left(imp_{i,t+1}^{CNUS} - imp_{i,t}^{CNUS}\right)}{L_{i,t}} \right),$$

where $imp_{i,t}^{CNMX}$ and $imp_{i,t}^{CNUS}$ indicate the value of imports from China to Mexico and the US, respectively, in industry i at time t.

5 Empirical results

In this section, I present the empirical results along with some robustness checks. Moreover, I discuss the implied quantitative magnitude of the impact of robots on employment in Mexico, and break it down by subgroups. Finally, I shed some light on the mechanism at work.

5.1 Regression results

The results from the ordinary least squares estimation that is the direct empirical counterpart of equation (11) are shown in Table 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level in all specifications.[15]

The baseline specification in column (1) includes only dummy variables for nine broad geographic regions as covariates. It shows a positive, insignificant coefficient for exposure to *domestic* robots on employment and a negative, significant one for exposure to *foreign* robots. In particular, an increase of one in a CZ's exposure to foreign robots is associated with a 27.7 percentage points smaller increase in the employment-to-population ratio between 1990 and 2015. As the average value of this exposure to foreign robots between 1993 and 2015 is 0.097, this implies a 2.7 percentage points lower employment-to-popluation growth for a CZ with average exposure. This estimate is significant at the 5% significance level. The results may, however, suffer from omitted variable bias, as they include only regional fixed effects as

[14] This implicitly assumes that each occupation within an occupation group has equal weight. While this may not be realistic, it seems to be the best solution, given the available data.

[15] Abadie et al. (2017) show that in models without fixed effects, a necessary condition for clustering standard errors is clustering in the assignment of a treatment. Figure A1 suggests that there is some geographical clustering in the treatment intensity.

covariates.

To account for this bias, I start by adding seven control variables that measure CZ-specific demographic characteristics in column (2). In particular, I add log population size, share of males, share of working-age population, share of population 65 or more years old, and the shares of people with primary, secondary and tertiary education as their highest degree, respectively. This slightly reduces the effect of foreign robots in absolute terms, and does not alter its significance.

Table 1: Impact of exposure to robots on employment (long difference)

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in employment-to-population ratio, 1990–2015					
Exposure to	1.157	1.306	1.067	0.755	0.597	1.116
domestic robots	(1.197)	(1.075)	(0.968)	(0.816)	(0.685)	(0.833)
Exposure to	-27.679**	-26.680**	-23.127**	-24.409**	-23.121**	-22.300**
foreign robots	(11.745)	(10.419)	(8.927)	(10.565)	(9.055)	(10.777)
R^2	0.424	0.468	0.501	0.520	0.557	0.474
Region dummies	✓	✓	✓	✓	✓	✓
CZ demographics		✓	✓	✓	✓	✓
Broad industry shares and import reliance of US			✓	✓	✓	✓
Computerization and Chinese trade competition				✓	✓	✓
Initial conditions					✓	
Remove top 1%						✓
Observations	1,806	1,806	1,806	1,806	1,806	1,793

Notes: The dependent variable is the change in the employment-to-working-age-population ratio between 1990 and 2015. Column (1) includes fixed effects for eight broad regions in Mexico. Column (2) also includes 1990 CZ demographics (i.e., log population size, share of men, share of working-age people, share of people 65 years or older, and the shares of people with primary, secondary and tertiary education as their highest degree, respectively). Column (3) also controls for several broad 1990 industry employment shares (i.e., shares of employment in manufacturing, light manufacturing, agriculture, construction, mining and services) as well as the initial exposure to US import reliance (see text for construction of this variable). Column (4) also controls for the share of routine jobs in 1990 following Autor and Dorn (2013) and exposure to Chinese import competition from 1990–2015, following Autor et al. (2013). Column (5) also includes the 1990 employment-to-population ratio. Column (6) excludes the top 0.5% of observations with respect to exposure to domestic and foreign robots, respectively. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Next, I include six initial broad industry shares in column (3) to allow for differential trends in certain broad industries in the same period. In particular, a CZ's initial share of employment in manufacturing, light manufacturing (defined as textiles as well as paper and printing, which were on a downward trend in the US for reasons unrelated to automation (cf. Acemoglu and Restrepo, 2017), agriculture, construction, mining and services are included.[16] Moreover, I include a measure of exposure to US import reliance as that is part of the interaction in the exposure to foreign robots variable, and should be included to rule out that changes

[16] Acemoglu and Restrepo (2017) also include the share of female employment in manufacturing. Doing so does not change the results, however, shrinks the sample by more than 10% as some CZs had no manufacturing employment in 1990, and thus the share of female employment in manufacturing is not computable. I therefore

in Mexican export capabilities or US import demand in general drive these results. These controls slightly reduce the effect of foreign robots in absolute size, leaving its significance level unchanged.

As mentioned before, a few other changes may have had an impact on employment between 1990 and 2015 while being correlated with the exposure to robots variables. To control for the most important ones, I thus include in column (4) the initial share of routine tasks as a measure of a CZ's exposure to computerization, and the exposure to Chinese import competition. Accounting for both of these contemporaneous changes does not significantly alter the results.

In column (5), I include the initial employment-to-population ratio to check for robustness against mean reversion. The data generating process of employment-to-population ratios may be mean-reverting. In that case, any CZs with temporarily high or low initial values would be likely to feature falling or rising employment-to-population ratios in the subsequent years, respectively. If these variations were correlated with the exposure to robots variables, the results may in reality be driven by mean reversion. Adding the initial conditions would capture such mean-reverting dynamics. Doing so also does not alter the qualitative or quantitative results. Thus I conclude that mean reversion seems not to be the driving force behind the results. Finally, column (6) excludes the top 0.5% of observations with respect to each exposure to robots variable. This is to rule out that the results are driven by a few outliers at the very top of the distribution. Doing so leaves the results unchanged.

Next, I run the same regression for two short differences to understand more about the timing of these estimated effects. The results are reported in Table 2, where Panels A and B show the results for the periods 1990–2000 and 2000–2015, respectively. The structure of all columns is identical to that of Table 1. Panel A suggests that domestic robots also had no effect on the employment to population ratio between 1990 and 2000, however, the effect of foreign robots is now positive in some specifications. While this result may be partly driven by measurement error in the exposure to robots variables for this period, it seems plausible. Robot adoption in Mexico was relatively low in the 1990s (cf. Figure 3), which is consistent with no detectable effects of domestic robots before 2000. Moreover, the number and quality of robots started their rapid increase only in the 2000s, potentially explaining why any robust effects of domestic and foreign robots are only visible after 2000. Another potential explanation for the non-negative effect of foreign robots from 1990 to 2000 is that in the middle of this period, in 1994, NAFTA came into effect, leading to an increase in exports to the US. As Mexican exports are concentrated in similar industries as US robots, this may have counteracted any negative effect US robots may have had. Panel B suggests that the the results from the long-difference specification before stem from the later period, 2000–2015. The pattern is similar and slightly more robust than the one shown in Table 1. In this later period, there is some evidence for a positive effect of domestic robots on employment,

do not include this measure.

although it is not robust across specifications. In general, these patterns suggest that in the early stages of robotic automation, its effect on employment outcomes was weak.

Table 2: Impact of exposure to robots on employment (short differences)

	(1)	(2)	(3)	(4)	(5)	(6)
	A. Change in employment-to-population ratio, 1990–2000					
Exposure to	-8.293	-2.707	-11.739	-11.438	-13.469	0.048
domestic robots	(9.090)	(8.208)	(7.619)	(8.706)	(8.804)	(12.164)
Exposure to	18.701	10.995	37.482**	44.864**	48.111**	8.691
foreign robots	(17.894)	(15.459)	(15.227)	(17.327)	(18.358)	(27.811)
	B. Change in employment-to-population ratio, 2000–2015					
Exposure to	0.797	0.682	1.638**	4.548**	3.511*	3.438
domestic robots	(0.692)	(0.748)	(0.733)	(2.027)	(2.063)	(2.083)
Exposure to	-14.116***	-13.120***	-18.714***	-32.821***	-27.044**	-25.701**
foreign robots	(2.881)	(3.116)	(3.641)	(10.591)	(10.821)	(10.981)
Region dummies	✓	✓	✓	✓	✓	✓
CZ demographics		✓	✓	✓	✓	✓
Broad industry shares and import reliance of US			✓	✓	✓	✓
Computerization and Chinese trade competition				✓	✓	✓
Initial conditions					✓	
Remove top 1%						✓
Observations	1,805	1,805	1,805	1,805	1,805	1,792

Notes: The dependent variables in Panels A and B are the change in the employment-to-working-age-population ratio between 1990 and 2000, and 2000 and 2015, respectively. Column (1) includes fixed effects for eight broad regions in Mexico. Column (2) also includes baseline CZ demographics (i.e., log population size, share of men, share of working-age people, share of people 65 years or older, and the shares of people with primary, secondary and tertiary education as their highest degree, respectively). Column (3) also controls for several baseline broad industry employment shares (i.e., shares of employment in manufacturing, light manufacturing, agriculture, construction, mining and services) as well as the initial exposure to US import reliance (see text for construction of this variable). Column (4) also controls for the share of routine jobs in the baseline year following Autor and Dorn (2013) and contemporaneous exposure to Chinese import competition, following Autor et al. (2013). Column (5) also includes the baseline employment-to-population ratio. Column (6) excludes the top 0.5% of observations with respect to exposure to domestic and foreign robots, respectively. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

The effect found in the long-difference estimation seems to stem from the later period, 2000–2015. For this reason, and to better purge the results from contemporaneous effects due to NAFTA, I focus on that period from now on. Next, I run the same regression, using the *exogenous exposure to robots variables* as described before. The main goal of using these variables is to rule out potential endogeneity caused by contemporaneous shocks to Mexican and US industries, or highly specialized Mexican commuting zones. The reduced form results are shown in Table 3, and are qualitatively similar to the OLS results.[17] This may have been expected as the endogenous exposure variables were already Bartik-style measures. These are often used as instruments themselves, as they abstract from variation caused by specific local

[17]See Table A2 in the Appendix for the first-stage OLS results.

conditions. Moreover, Panel B of Figure 2 showed that the industry variation of US robots is very similar to that in the rest of the world, and thus does not seem to be particularly affected by Mexican labor market conditions. The results therefore suggest that endogeneity concerns affecting industry variation seem not to cause a large bias in the prior results. To bolster confidence that this result is not driven by a few outliers or a certain combination of covariates, the raw residual plot of the change in the employment to population ratio and exogenous exposure to foreign robots is shown in Figure 5.

Table 3: Impact of exposure to robots on employment (reduced form)

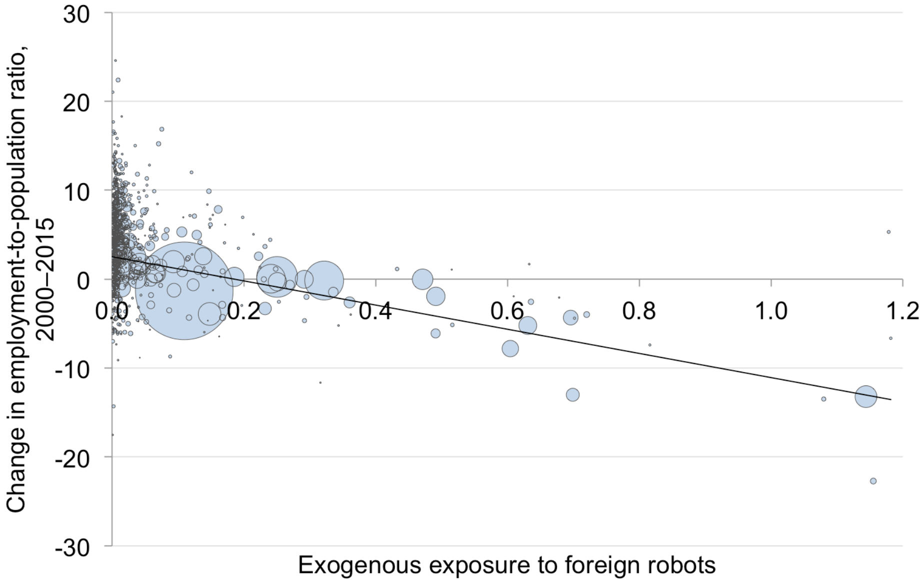
	(1)	(2)	(3)	(4)	(5)	(6)
	Change in employment-to-population ratio, 2000–2015					
Exogenous exposure to *domestic* robots	-0.740	-0.764	-0.560	1.258	1.094	1.167
	(0.506)	(0.525)	(0.523)	(0.752)	(0.784)	(0.759)
Exogenous exposure to *foreign* robots	-9.377***	-8.646**	-12.995***	-28.901***	-25.697***	-24.312***
	(3.397)	(3.507)	(3.378)	(7.376)	(7.646)	(6.973)
Region dummies	✓	✓	✓	✓	✓	✓
CZ demographics		✓	✓	✓	✓	✓
Broad industry shares and import reliance of US			✓	✓	✓	✓
Computerization and Chinese trade competition				✓	✓	✓
Initial conditions					✓	
Remove top 1%						✓
Observations	1,805	1,805	1,805	1,805	1,805	1,792

Notes: The dependent variable is the change in the employment-to-working-age-population ratio between 2000 and 2015. Column (1) includes fixed effects for eight broad regions in Mexico. Column (2) also includes 2000 CZ demographics (i.e., log population size, share of men, share of working-age people, share of people 65 years or older, and the shares of people with primary, secondary and tertiary education as their highest degree, respectively). Column (3) also controls for several broad 2000 industry employment shares (i.e., shares of employment in manufacturing, light manufacturing, agriculture, construction, mining and services) as well as the initial exposure to US import reliance (see text for construction of this variable). Column (4) also controls for the share of routine jobs in 2000 following Autor and Dorn (2013) and exposure to Chinese import competition from 2000–2015, following Autor et al. (2013). Column (5) also includes the 2000 employment-to-population ratio. Column (6) excludes the top 0.5% of observations with respect to exposure to domestic and foreign robots, respectively. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Identification using these instruments rests on a few assumptions: First, and most importantly, local initial employment shares in the industries driving the difference between both exposure to robots variables are assumed to be uncorrelated with the error term.[18] In the instruments of both exposure to robots variables, I do not instrument for the initial employment shares, although they drive part of the variation. Any correlation of the initial shares with the error term may thus threaten identification. While it is impossible to test for their correlation with unobservables, one can at least test whether CZs that have the largest difference in the exposure to domestic relative to foreign robots have similar observable characteristics. Columns Q1 to Q4 in Table A1 report summary statistics of selected covariates used in the specifications, ranging from the quartile of CZs relatively most exposed to foreign robots (Q1) to the one relatively most exposed to domestic robots (Q4). It is reassuring that

[18] As discussed and formally shown in Goldsmith-Pinkham et al. (2018), the key identifying assumption

the averages in the first and fourth quartile are not significantly different from each other for all but two of the 17 observable characteristics I include, namely the share of males and the exposure to Chinese import competition.



Note: This figure presents residual plot of the change in the employment-to-population ration and the exposure to domestic and foreign robots, respectively. Bubble size indicates a CZ's share of the overall working-age population. The black lines represents the fitted line without partialling out any covariates, using 1990 working-age population as weights.

Figure 5: Relationship between employment-to-population ratio and exogenous exposure to foreign robots, 2000–2015

Second, the adoption of robots in countries outside of Mexico and the US is assumed to be unrelated to local labor market conditions in Mexico. In reality, industries across countries are in competition with one another. Local labor market conditions in Mexico may thus affect Mexican and US robot adoption, which in turn may affect world robot adoption. In this story, the reverse causality would carry all the way through to the instrument. While it is certainly true that industries are in competition with each other across countries, the fact that Mexico exported relatively little to the 19 countries used in the instrument makes this scenario somewhat unlikely.

Third, I assume that there has been no global shock differentially affecting industries across the world in the same way as robots. This scenario cannot be fully ruled out. In an attempt to control for the arguably two most important such candidates, I control for routine share intensity (computerization) and Chinese import competition also in the reduced form specifications from column (4) onwards. Moreover, I include robots in the most highly-robotized industry, automotive, separately in the robustness checks below. The results for the effect of foreign robots are robust against this, thus not lending support to this alternative explana-

using Bartik-style instruments is best stated in terms of initial shares tion.

5.2 Robustness checks

In this subsection, I perform robustness checks against some alternative explanations. To start with, I examine the period between 1970 to 1990 to rule out that these coefficients are driven by long-run negative employment trends in precisely those industries that had the largest increase in robot usage abroad. I therefore estimate the identical regressions as in Table 1, only that now the dependent variable is the *1970–1990*, and not the 1990–2015 change in the employment-to-population ratio. As I argued before, the numbers of robots in Mexico and the US were likely close to zero in the period before 1990. Hence, the results should show no effect of exposure to robots on employment. The results are reported in Table 4.

Table 4: Impact of exposure to robots on employment (pre-exposure)

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in employment-to-population ratio, 1970–1990					
Future exogenous exposure to *domestic* robots, '93–'15	0.261	0.145	0.047	0.094	-0.409	0.342
	(1.141)	(1.005)	(0.872)	(0.853)	(0.697)	(0.880)
Future exogenous exposure to *foreign* robots, '93–'15	10.919*	5.845	9.289	8.040	11.114**	2.129
	(6.233)	(6.591)	(5.578)	(5.555)	(4.665)	(5.677)
R^2	0.253	0.353	0.426	0.426	0.657	0.470
Region dummies	✓	✓	✓	✓	✓	✓
CZ demographics		✓	✓	✓	✓	✓
Broad industry shares and import reliance of US			✓	✓	✓	✓
Computerization and Chinese trade competition				✓	✓	✓
Initial conditions					✓	
Remove top 1%						✓
Observations	1,789	1,789	1,786	1,786	1,786	1,773

Notes: The dependent variable is the change in the employment-to-working-age-population ratio between 1970 and 1990. Column (1) includes fixed effects for eight broad regions in Mexico. Column (2) also includes 1970 CZ demographics (i.e., log population size, share of men, share of working-age people, share of people 65 years or older, and the shares of people with primary, secondary and tertiary education as their highest degree, respectively). Column (3) also controls for several 1970 broad industry employment shares (i.e., shares of employment in manufacturing, light manufacturing, agriculture, construction, mining and services) as well as the initial exposure to US import reliance (see text for construction of this variable). Column (4) also controls for the share of routine jobs in 1970 following Autor and Dorn (2013) and exposure to Chinese import competition from 1990–2015, following Autor et al. (2013). Column (5) also includes the 1970 employment-to-population ratio. Column (6) excludes the top 0.5% of observations with respect to exposure to domestic and foreign robots, respectively. All regressions are weighted by working-age population in 1970. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

It is reassuring that almost all coefficients on the exposure to robots variables are insignificant. However, the exposure to foreign robots variable is positive and slightly significant in columns (1) and (5). This has a plausible explanation: If the exposure to foreign robots captures any effects of *reshoring*, it is likely to capture the effects of *offshoring* in the pre-period. In the late 1960s, Mexico introduced their *Maquiladora* program, which allowed the duty-free import of materials for assembly and subsequent export of the manufactured goods, and is to a large extent responsible for Mexico's status as a typical manufacturing offshoring country today. The positive coefficient on the exposure to foreign robots thus likely captures the effects of that program. Moreover, this relationship is strengthened by a mechanical correlation: The exposure to foreign robots variable includes a US industry's reliance on Mexican imports in 1992, which is part of the outcome variable in this specification.[19] Finally, this evidence suggests that the industries most affected by foreign robots had been, if at all, on the *opposite* trend prior to robotization. Hence, the results of this exercise lend no support to the view that pre-existing trends are responsible for the results.

Table 5: Impact of exposure to robots on employment (controlling for automotive)

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in employment-to-population ratio, 2000–2015					
Exog. exp. to *domestic* robots in other industries	-0.242	0.720	-0.330	-1.758	-0.625	-1.338
	(1.258)	(1.073)	(1.612)	(1.852)	(1.557)	(1.993)
Exog. exp. to *foreign* robots in other industries	-10.520***	-11.706***	-13.357***	-33.268***	-28.219***	-28.967***
	(3.467)	(3.165)	(4.003)	(8.747)	(9.505)	(8.731)
Exog. exp. to robots in automotive industry	-1.872***	-1.881***	-2.066***	-2.246***	-1.978***	-1.799***
	(0.172)	(0.183)	(0.283)	(0.278)	(0.306)	(0.282)
R^2	0.469	0.493	0.514	0.527	0.601	0.403
Region dummies	✓	✓	✓	✓	✓	✓
CZ demographics		✓	✓	✓	✓	✓
Broad industry shares and import reliance of US			✓	✓	✓	✓
Computerization and Chinese trade competition				✓	✓	✓
Initial conditions					✓	
Remove top 1%						✓
Observations	1,805	1,805	1,805	1,805	1,805	1,792

Notes: All specifications are identical to Table 3, except that automotive robots are excluded from the exposure to robots variables and included as a separate measure.

The use of robots per worker has increased the most in the automotive industry. It is therefore possible that much of the effect of robots found before is, in reality, due to some other shock that has affected the automotive industry in the same period. To test for this, I exclude robots used in automotive manufacture from both exposure to robots variables, and include them as a separate measure named *exposure to robots in automotive industry.*[20] In case the effects found so far were indeed driven by other shocks to the automotive industry, the new *exposure to robots in other industries* variables should show no effect. Table 5 presents the results of this exercise. The coefficient of the *exposure to domestic robots in other industries* is not significantly different from zero in any of the specifications. The

[19]Ideally, I would use the 1970 reliance on Mexican imports to circumvent this issue, but such data only exists from 1992 onwards.

[20]Note that in this setting, it is impossible to separately estimate coefficients for the exposure to domestic

coefficient of the *exposure to foreign robots in other industries* variable is still negative and significant throughout all specifications. It is, reassuringly, similar in absolute size as that of the previous variable including automotive robots (–33.3 compared to –28.9 in column (4) of Table 3). This suggests that robots are, in fact, a similar technology across industries, without much variation in their relative productivity and that robots in different industries are substitutes for Mexican workers to a similar degree.

Table 6: Impact of exposure to robots on employment and population

	(1)	(2)	(3)	(1)	(2)	(3)
	A. Δ log employment, 00–15			*B. Δ log working-age, 00–15*		
Exposure to *domestic* robots	0.056 (0.042)	0.046 (0.042)	0.051 (0.037)	0.028 (0.032)	0.027 (0.032)	0.027 (0.031)
Exposure to *foreign* robots	-1.122*** (0.370)	-0.958** (0.384)	-0.889** (0.350)	-0.424 (0.266)	-0.416 (0.266)	-0.295 (0.274)
Baseline covariates	✓	✓	✓	✓	✓	✓
Computerization and Chinese trade competition	✓	✓	✓	✓	✓	✓
Initial conditions		✓			✓	
Remove top 1%			✓			✓
Observations	1,805	1,805	1,792	1,805	1,805	1,792

Notes: The dependent variable in Panel A is the change in the log of the employment count between 2000 and 2015, in Panel B the change in the log of the working-age population between 2000 and 2015. Column (1) includes fixed effects for eight broad regions in Mexico, 2000 CZ demographics (i.e., log population size, share of men, share of working-age population, share of people 65 years or older, and the shares of people with primary, secondary and tertiary education as their highest degree, respectively) and 2000 industry employment shares (i.e., shares of employment in manufacturing, light manufacturing, agriculture, mining, construction and services), exposure to US import reliance, the share of routine jobs in 2000 following Autor and Dorn (2013) and exposure to Chinese import competition from 2000–2015, following Autor et al. (2013). Column (2) also controls for the initial conditions with respect to the outcome variable. Column (3) is the same specifications as column (1), but excludes the top 0.5% of observations with respect to exposure to domestic and foreign robots. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

The dependent variable in all specifications so far was the change in the employment-to-population ratio, as this is the standard measure used in this literature. However, changes in this ratio may arise from changes in employment or changes in the working-age population. The model predicts changes in employment, and the use of CZs is motivated by low rates of migration across CZs. It is useful to test the model's implication and implicit assumption when using CZs by estimating the model using the log employment count and the log working-age population as the dependent variable. This is done in Panels A and B of Table 6, respectively. The results show that the effect stems, in fact, from changes in employment and not in the working-age population. Moreover, the point estimates in Panel B provide suggestive evidence that there may be some migration response to worsened labor market conditions due to foreign robots.

Finally, it is important to rule out that the negative coefficient on the exposure to foreign robots variable is solely driven by variation in the reliance on Mexican imports, F_i. If this were the case, these results may rather be caused by changes in US demand or Mexico's export capacities in general than US robots. In the previous analyses, I control for the exposure to US import reliance from column (3) onwards. Another way to test for this is to exclude US import reliance ($F_{i,t}$) from the exposure to foreign robots variable. Although I prefer keeping it in as it seems more sensible from a theoretical perspective, it is reassuring that leaving it out does not alter the qualitative results (cf. Figure A3 in the Appendix).

5.3 Quantitative magnitude

Next, I turn to the quantitative magnitude of the impact of robots on employment in Mexico. Note that the empirical specifications include only a CZ's *exposure to* robots, not the number of installed robots directly. Hence, the clean interpretation of the coefficients only allows for conclusions about employment-to-population ratio growth in CZs initally *specialized* in certain industries, not about the number of workers each robot substitutes for directly. I will, however, shortly discuss the implied magnitudes for the latter as well, for the hypothetical scenario that the exposure to robots variables perfectly measure a CZ's actual number of robots competing with labor. Moreover, note that these estimates only measure the effect of robots on *local* employment. In particular, they do not account for positive spillovers resulting from reductions in the overall price level from the use of robots in other CZs. The aggregate implications stated here are thus under the assumption that these spillovers are low.[21]

I run the two-stage least squares counterpart to Table 3, but now using the change in the *engagement*-to-population ratio as the dependent variable (i.e., including self-employed and public sector employees) to assess the quantitative magnitude of the effect of foreign robots on overall engagement. This allows for take-up of displaced employed workers as self-employed workers, laborers or public administrators, and is more informative to gauge the aggregate effect. Table 7 presents the results of this estimation. I focus on the results for foreign robots, as I cannot rule out that the ones for domestic robots are purely driven by the automotive industry.

The coefficient in my preferred specification in column (5) implies that an increase in the exposure to foreign robots of one reduces the employment-to-population ratio growth by 20 percentage points. The average value of this variable is around 0.143. Hence, a CZ with the average exposure to foreign robots experienced a 2.85 percentage points lower growth in the employment-to-population ratio. If we assume that US robots are the only foreign robots substituting for Mexican labor, this implies that the roughly 145,000 robots that were added in the US between 2000 and 2015 reduced engagement in Mexico by about 1.7 million workers, or that one US robot reduced engagement in Mexico by about 11.5 workers.

These estimates are larger than the ones estimated by Acemoglu and Restrepo (2017), who

and foreign robots in the automotive industry, as they only differ by the factor F_i and are thus collinear.

[21] Acemoglu and Restrepo (2017) use the structure of their model to back out the aggregate effect. In their setup, such spillovers reduce the negative effect by about 10%.

find that each robot reduces employment by 6 workers, but not implausible given the lower productivity of Mexican workers as compared to US workers (i.e., parameter γ in the model). More importantly, it rests on the assumption that *all* 145,000 US robots substitute for Mexican labor, and not just a fraction of them, as assumed in the theory. This implies that each task performed by US robots nowadays either previously *was* or *would have been* done by humans in Mexico, if robots had not emerged. If this were true, this also means that these robots cannot, at the same time, substitute for US labor. But this is precisely the assumption behind the results of Acemoglu and Restrepo (2017). The truth is likely to lie somewhere in between, with some US robots being substitutes for US labor, and some being substitutes for Mexican labor. Any such correction, however, proportionally increases both estimates, as the numbers of substituted workers are then divided by fewer robots.

Table 7: Impact of exposure to robots on engagement (IV)

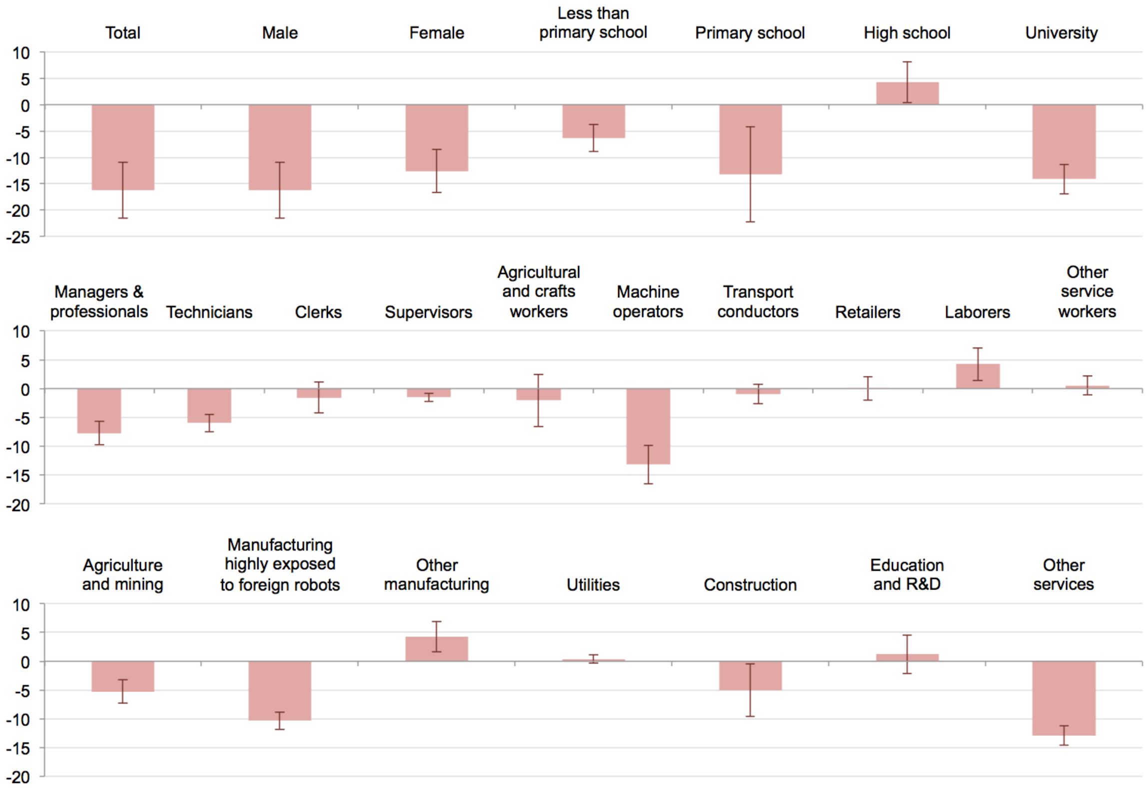
	(1)	(2)	(3)	(4)	(5)	(6)
	Change in engagement-to-population ratio, 2000–2015					
Instrumented exposure to *domestic* robots	3.397** (1.331)	3.115*** (1.130)	3.416*** (0.997)	4.629** (2.098)	4.094** (2.050)	4.812** (2.330)
Instrumented exposure to *foreign* robots	-13.183*** (4.497)	-15.147*** (4.312)	-17.042*** (3.980)	-22.472** (9.846)	-20.017** (9.505)	-24.013** (11.392)
First-stage F-statistics						
– *domestic*	204.3	345.5	677.1	65.6	65.3	44.7
– *foreign*	261.4	499.1	1201.6	62.0	61.8	44.8
– Kleibergen-Paap	99.1	139.5	246.0	30.2	30.2	22.3
Region dummies	✓	✓	✓	✓	✓	✓
CZ demographics		✓	✓	✓	✓	✓
Broad industry shares and import reliance of US			✓	✓	✓	✓
Computerization and Chinese trade competition				✓	✓	✓
Initial conditions					✓	
Remove top 1%						✓
Observations	1,805	1,805	1,805	1,805	1,805	1,792

Notes: All specifications are identical to Table 3, except that now the exogenous exposure to robots variables are used as instruments in a two-stage least square estimation, and the dependent variable now includes self-employed and public-sector employees.

Note, however, that it may not just be US robots substituting for Mexican labor, but also those of other developed countries such as Canada that might have offshored production to Mexico, if robots had not been invented. Other potential explanations for this somewhat large estimate are closer substitutability between US robots and Mexican workers (i.e., a higher F_i) or other incentives for reshoring being correlated with robot adoption across industries.

5.4 Effects by subgroup

In the following I break down the effect for the aggregate into subgroups of workers. In particular, I reestimate column (4) of Table 3, but now with subgroup-employment-to-population ratios as the dependent variable. Figure 6 presents the results of this exercise. The thick bars represent point estimates of the coefficient on exogenous exposure to foreign robots. The thin lines on top of each bar correspond to its standard error. The upper panel presents estimates by gender and education, the middle one by occupation and the lower one by industry.



Notes: This figure plots the point estimates (thick bars) and standard errors (thin bars) of the exogenous exposure to foreign robots variable on different employment-to-population ratios. The specification is identical to the one in column (4) in Panel B of Table 2, with the only difference that the dependent variables are now subgroup-specific employment-to-population ratios. The upper panel presents estimates by gender and education. The middle panel shows estimates by occupation. The lower panel presents estimates by industry. For example, in the second set of bars in the upper panel, the dependent variable is the change in male employment over the entire working-age population in a CZ between 2000 and 2015.

Figure 6: Impact of exposure to robots on employment by gender, education, occupation and industry

The effect of foreign robots is slightly more pronounced for men than for women, and strongest for those with primary school and university education. There is a small but insignificant positive effect on individuals with a high-school diploma. This may reflect the reverse mechanism of Atkin (2016), i.e., reduced opportunity costs of staying in school for prospective high-school dropouts due to worsened labor market conditions from lower offshoring activities. In terms of occupations, the effect stems mostly from machine operators, and the effect on university-educated workers is mirrored in the estimates for managers and professionals as well as technicians. There is a slight positive effect on employment of laborers, which might reflect some take-up of displaced machine operators. The effects across industries paint a similar picture, with the strongest negative effects in manufacturing industries that were highly exposed to US robots (i.e., automotive, electronics, metal products and minerals) and services, and slight negative effects in agriculture and mining as well as construction. The small positive effect on laborers is mirrored in a small increase in the employment in other, less robotized manufacturing industries.

While it is easy to imagine that robots have an effect on less-educated workers in machine operating occupations, it is not as clear why it should have such a strong effect on university-educated workers in managerial and professional occupations. Potential reasons for this are either above average employment of university-educated people and managers in the exports-producing sector or positive spillovers into such sectors. Cañas et al. (2013) provide some support for the latter, i.e., that Maquiladora production has particularly strong spillovers into the service sector (in particular transportation, finance, insurance, real-estate, legal and accounting).

Overall, the results from this analysis suggest that two groups of workers were negatively affected by foreign robots: First, less-educated machine operators and technicians in the manufacturing sector, and second, highly-educated managers and professionals in the service industry. From these results, it seems that the former group may have more successfully managed to sort into related occupations (laborers in less robotized manufacturing industries) than the latter.

5.5 Mechanism

If the reduction in employment due to foreign robots is indeed driven by reshoring, one should see a similar response in exports from Mexico to the US. To check for this, I use a Bartik-style measure of the change in Mexican exports to the US per worker between 2000 and 2015 as a dependent variable in Panel A of Table 8.

The results support the narrative that foreign robots reduce the volume of exports, and thereby employment in the affected CZs. On a national level, the estimates in column (2) suggest that annual exports were roughly USD 34 billion lower as a result of foreign robots. On average between 2007 and 2015, a Maquiladora – a Mexican export manufacturing firm exempt from tariffs on imported inputs, and a main driver of Mexico's status as an offshoring country[22] – produced USD 15 million worth of exports utilizing about 380 employees.[23] Hence, each employee contributed roughly USD 40,000 worth of exports. The estimated reduction of USD 34 billion in exports thus translates into about 860,000 fewer employees, or about 50% of the total effect found for employment directly. Note, however, that the standard errors in this specification must be interpreted with caution, as both the dependent and explanatory variables of interest are based on the same initial employment shares.

[22] Maquiladoras made up about 45% of Mexican exports in 2006

[23] Based on INEGI EMIME data.

Table 8: Impact of exposure to robots on exports and Maquiladoras

	(1)	(2)	(3)	(1)	(2)	(3)
	A. Δ Exports per cap., 00–15			*B. Δ Maq.'s per cap., 07–15*		
Exposure to *domestic* robots	5.413***	5.409***	5.366***	0.033**	0.046**	0.043**
	(0.248)	(0.247)	(0.260)	(0.012)	(0.017)	(0.016)
Exposure to *foreign* robots	-11.335***	-11.298***	-11.164***	-0.110*	-0.166*	-0.190**
	(1.223)	(1.242)	(1.285)	(0.063)	(0.089)	(0.091)
Baseline covariates	✓	✓	✓	✓	✓	✓
Computerization and Chinese trade competition	✓	✓	✓	✓	✓	✓
Initial conditions		✓			✓	
Remove top 1%			✓			✓
Observations	1,805	1,805	1,792	1,791	1,791	1,778

Notes: The dependent variable in Panel A a Bartik-style measure of the change in exports to the US in thousand USD between 2000 and 2015 per worker in 2000, and in Panel B the change in the number of Maquiladora factories between 2007 and 2015 per working-age person in 2000. The covariates in columns (1) to (3) are identical to Table 6. Column (1) includes fixed effects for eight broad regions in Mexico, 2000 CZ demographics (i.e., population size, share of population that is working-age, and the shares of people with secondary and tertiary education as their highest degree, respectively) and 2000 industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, construction and agriculture) as well as exposure to contemporaneous changes (share of routine tasks in 2000 and contemporaneous Chinese import competition, see text for construction of these variables). Column (2) also controls for the initial conditions with respect to the outcome variable. Column (3) is the same specifications as column (1), but excludes the top 1% of observations with respect to exposure to domestic and foreign robots. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Another way to test for this is to look at the effect on the number of Maquiladora factories. Panel B uses the change in the number of Maquiladoras between 2007 and 2015 per 1,000 working-age people as the dependent variable.[24] Areas more exposed to foreign robots experienced a significant fall in the number of Maquiladoras per person. The magnitude of the estimates in column (1) implies that a CZ with an average exposure to foreign robots experienced a decline in its number of Maquiladoras of 0.76, or 25%. Nationally, this translates into a reduction by 1370 such factories. Given that the average Maquiladora employs roughly 380 workers, this reduction between 2007 and 2015 seems to account for about 520,000 of the 1.7 million fewer jobs between 2000 and 2015.

6 Conclusion

In this paper, I investigate the impact of industrial robots on employment in an offshoring country, using the example of Mexico. Robots may have a distinct impact on employment in offshoring countries, as they potentially fuel reshoring by reducing the relative cost of domestic production in developed countries. Despite an increasing anecdotal evidence for reshoring, there exists no empirical analysis of the effect of robots on employment in offshoring countries

[24]Data on the number of Maquiladoras between 2007 and 2015 is available on three levels of geographic granularity. First, at the CZ level for those with the most Maquiladoras per capita, second, on the state level for those with fewer ones, and third, on a national level for the remaining states with almost none. In order to get estimates of the number of Maquiladoras per capita by CZ also for those with no detailed information, I subdivide the remaining CZs into two groups (with information by state and by country, respectively) and allocate the respective number of Maquiladoras in a Bartik-style manner among the CZs in each group according to their initial share of manufacturing employment within that group.

so far.

Following a recent literature, I use a model in which robots compete against human labor to analyze the effect of both *domestic* and *foreign* robots on employment. In the basic model without trade across countries, the effect of domestic robots on employment in a local labor market depends linearly on its *exposure to domestic robots*, defined from the penetration of domestic robots into each industry, weighted by its initial share of the respective industry's national employment. In light of the emergence of reshoring, I consider also an exports-producing sector, which may be affected by foreign robots. The effect of foreign robots on employment in a local labor market is identified via its *exposure to foreign robots*, defined from the penetration of foreign robots into each industry, weighted by its initial share of the respective industry's national employment, and by the foreign industries' initial reliance on imports from the home country.

Data from the IFR and Mexican censuses allow me to construct empirical counterparts to these theoretical measures. In the baseline specification, I regress changes in the employment-to-population ratio between 1990 and 2015 on these exposure-to-robots variables. Using this methodology, I find large negative and robust effects of foreign robots on employment. This effect stems from the later period in the sample, 2000–2015, and is not visible in the period from 1990–2000. It is robust to allowing for differential trend regarding a number of covariates, including region dummies, CZ demographics, broad industry shares, exposure to computerization and Chinese import competition as well as initial conditions.

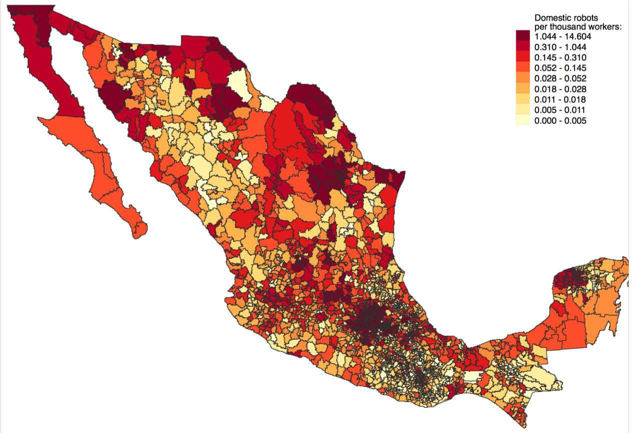
In principle, these results may suffer from endogeneity caused by contemporaneous shocks to US and Mexican industries or specialized local labor markets, such as the introduction of NAFTA. To purge them of bias caused by such endogeneity or measurement error, I apply an instrumental variable strategy, using increased use of robots in the rest of the world (i.e., outside of the US and Mexico) as an instrument for US and Mexican robots. Doing so does not change the results, suggesting that these endogeneity and measurement error concerns do not cause a large bias.

Moreover, I perform robustness checks to rule out alternative explanations. First, preexisting trends in industries, in which robots are most heavily used, seem not to be the driving force. A pre-period analysis, looking at the pre-period 1970–1990, does not provide evidence for this alternative explanation. Second, the results for the effect of foreign robots are not only driven by the automotive industry, the industry robots are most prevalent in. Third, the effect is indeed driven by reduced employment, not any underlying migration patterns. Fourth, the effect does not stem from changes in Mexican export capabilities in general. Finally, the employment effects are mirrored by similar reductions in the export volume and the number of Maquiladoras, Mexican exports-manufacturing factories.

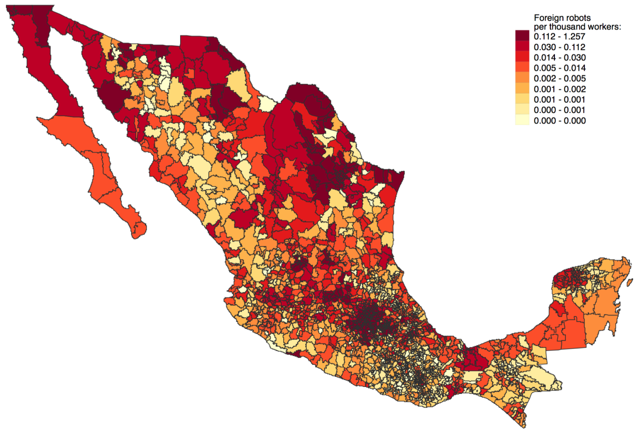
With regard to the quantitative magnitude of the effect, a local labor market with an average exposure to foreign robots experienced a 2.9 percentage points lower growth in the employment-to-population ratio, compared with no such exposure. At the national level, this amounts to roughly 1.7 million fewer jobs in Mexico, implying that one US robot substitutes for roughly 11 Mexican workers. This seems quite high, given existing estimates of one US robot simultaneously substituting for 6 US workers. While this presents a challenge and needs further investigation, lower productivity of workers in offshoring countries, robots in other destination markets contributing to this number, closer substitutability between robots and Mexican workers, other technological changes happening as a result of employing robots, and other incentives for reshoring being correlated with robots may contribute to these larger estimates. Understanding the drivers behind the magnitude of this effect needs to be analyzed in more detail. Moreover, alternative strategies to estimate the aggregate implications of this (e.g., cross-country comparisons) are obviously highly complementary to this within-country comparison approach.

These limitations notwithstanding, the empirical results of this paper are at least worrying for offshoring and developing countries. Robot stocks in the developed world are expected to be three times as high as today by 2025, which will likely fuel reshoring (BCG, 2015, p.7). Such rapid changes in employment patterns have been shown to foster political polarization in the United States (Autor et al., 2016). Given offshoring countries' combined population of about 3 billion, or 40% of the world's population, robotization in developed countries seems to pose a threat to labor markets and, in turn, political stability, in the developing world. This paper offers first insights about potential causes of such instabilities. These may help to inform the debate about how to prevent or at least mitigate such effects.

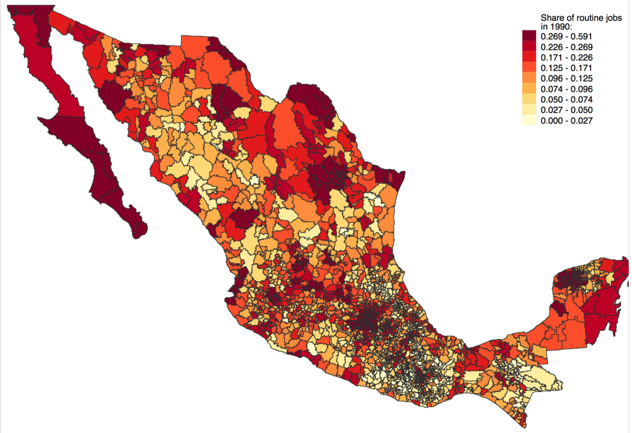
A Appendix



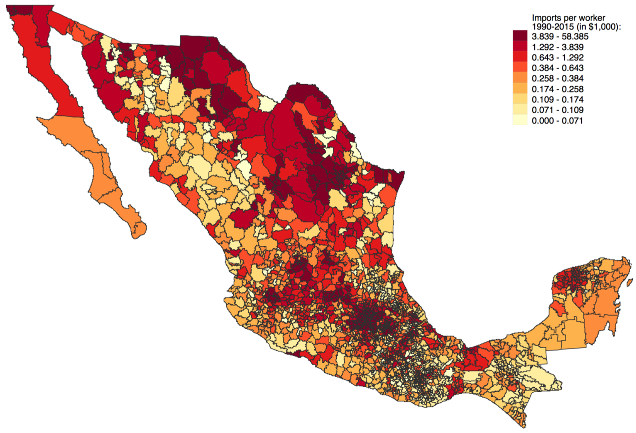
(a) Exposure to domestic robots, 1993–2015



(b) Exposure to foreign robots, 1993–2015



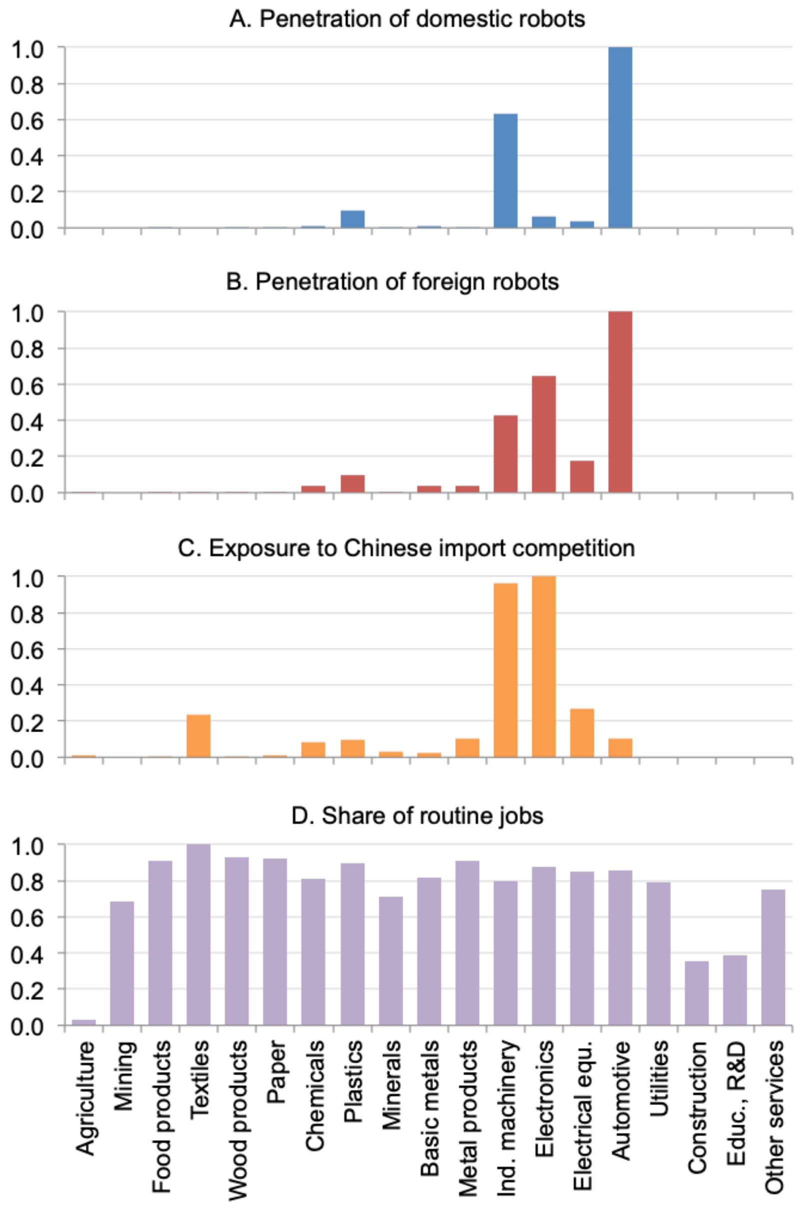
(c) Share of routine jobs, 1990



(d) Exposure to Chinese import competition, 1992–2015

Figure A1: Commuting Zone-level variation in exposures to domestic and foreign robots, computerization and Chinese import competition

Figure A2: Industry-level variation in increase in domestic robots, foreign robots, US exports and Chinese imports per worker, and offshorability and computerization



Note: Panel A presents the 2000–2015 increase in robots per worker in Mexico. Panel B shows the 2000–2015 increase in robots in the US per Mexican worker multiplied by each US industry's reliance on Mexican imports in 2000. Panel C presents the 2000–2015 increase in Chinese imports per worker (as defined in the text above). Panel D presents the share of routine jobs per industry in 2000 (following Autor and Dorn (2013)). All variables are normalized such that the industry with the highest value gets a value of one and the lowest gets a value of zero.

Table A1: Summary statistics

		Difference between standardized exposure to domestic and foreign robots			
	All CZs	Q1	Q2	Q3	Q4
		Panel A. Outcomes			
Change in outcome (2000–15)					
Employment-to-population ratio	0.796	0.336	2.718	3.914	0.041
	[4.125]	[4.588]	[4.635]	[4.190]	[3.008]
Log employment count	0.319	0.336	0.402	0.421	0.263
	[0.203]	[0.173]	[0.324]	[0.266]	[0.152]
Log working-age population	0.278	0.312	0.275	0.266	0.255
	[0.123]	[0.112]	[0.164]	[0.178]	[0.097]
		Panel B. Explanatory variables			
Exposure to robots (2000–15)					
Domestic minus foreign	-0.092	-0.399	0.011	0.021	0.074
	[0.519]	[0.602]	[0.002]	[0.003]	[0.131]
Domestic	0.551	0.770	0.048	0.040	0.597
	[0.857]	[1.105]	[0.123]	[0.032]	[0.717]
Foreign	0.143	0.232	0.011	0.008	0.130
	[0.223]	[0.303]	[0.028]	[0.007]	[0.152]
CZ demographics (2000)					
Share of men	0.487	0.489	0.491	0.487	0.484
	[0.011]	[0.011]	[0.015]	[0.016]	[0.008]
Working-age share	0.592	0.594	0.545	0.552	0.608
	[0.047]	[0.038]	[0.049]	[0.046]	[0.041]
Share with primary education*	0.513	0.526	0.443	0.459	0.531
	[0.063]	[0.052]	[0.078]	[0.067]	[0.048]
Share with secondary education*	0.155	0.158	0.096	0.105	0.177
	[0.062]	[0.050]	[0.066]	[0.060]	[0.055]
Share with tertiary education*	0.077	0.080	0.041	0.048	0.089
	[0.039]	[0.037]	[0.036]	[0.036]	[0.034]
Broad industry shares (2000)					
Manufacturing	0.181	0.215	0.093	0.091	0.192
	[0.094]	[0.102]	[0.073]	[0.056]	[0.071]
Light manufacturing	0.047	0.046	0.025	0.023	0.058
	[0.050]	[0.045]	[0.041]	[0.035]	[0.054]
Agriculture	0.178	0.150	0.429	0.355	0.110
	[0.210]	[0.169]	[0.255]	[0.228]	[0.158]
Construction	0.079	0.084	0.073	0.085	0.076
	[0.028]	[0.023]	[0.039]	[0.040]	[0.024]
Exposure to contemporaneous changes					
Share of routine jobs (2000)	0.241	0.259	0.158	0.176	0.260
	[0.073]	[0.066]	[0.077]	[0.073]	[0.056]
Chinese import comp. (2000–15)	2.325	3.972	0.411	0.316	1.869
	[2.641]	[3.632]	[0.464]	[0.257]	[0.981]
Initial conditions (2000)					
Employment-to-population ratio	36.745	39.859	26.946	28.397	38.194
	[9.298]	[8.696]	[11.218]	[10.079]	[6.195]

Note: To define Q1 to Q4, I first standardized both exposure to robots variables to have a mean of zero and standard deviation of one, and then computed the difference of the standardized exposures to domestic minus foreign robots.

*As highest degree obtained.

Table A2: First-stage OLS regression results

	(1)	(2)	(3)	(4)	(5)	(6)
	A. Exposure to domestic robots, 2000-15					
Exogenous exposure to *domestic* robots	1.087***	1.069***	1.115***	0.876***	0.875***	0.851***
	(0.062)	(0.051)	(0.032)	(0.062)	(0.062)	(0.069)
Exogenous exposure to *foreign* robots	-1.975***	-1.798***	-1.401***	0.731	0.747	1.062*
	(0.346)	(0.280)	(0.187)	(0.552)	(0.551)	(0.593)
First-stage F-statistic	204.3	345.5	677.1	65.6	65.3	44.7
	B. Exposure to foreign robots, 2000-15					
Exogenous exposure to *domestic* robots	0.123***	0.121***	0.126***	0.094***	0.094***	0.093***
	(0.006)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
Exogenous exposure to *foreign* robots	0.496***	0.530***	0.593***	0.880***	0.882***	0.888***
	(0.032)	(0.022)	(0.014)	(0.028)	(0.028)	(0.029)
First-stage F-statistic	261.4	499.1	1201.6	62.0	61.8	44.8
Region dummies	✓	✓	✓	✓	✓	✓
CZ demographics		✓	✓	✓	✓	✓
Broad industry shares and import reliance of US			✓	✓	✓	✓
Computerization and Chinese trade competition				✓	✓	✓
Initial conditions					✓	
Remove top 1%						✓
Observations	1,805	1,805	1,805	1,805	1,805	1,792

Notes: The dependent variable in Panel A and B is the exposure to domestic and foreign robots between 2000 and 2015, respectively. Column (1) includes fixed effects for eight broad regions in Mexico. Column (2) also includes 2000 CZ demographics (i.e., log population size, share of men, share of working-age people, share of people 65 years or older, and the shares of people with primary, secondary and tertiary education as their highest degree, respectively). Column (3) also controls for several broad 2000 industry employment shares (i.e., shares of employment in manufacturing, light manufacturing, agriculture, construction, mining and services) as well as the initial exposure to US import reliance (see text for construction of this variable). Column (4) also controls for the share of routine jobs in 2000 following Autor and Dorn (2013) and exposure to Chinese import competition from 2000–2015, following Autor et al. (2013). Column (5) also includes the 1990 employment-to-population ratio. Column (6) excludes the top 0.5% of observations with respect to exposure to domestic and foreign robots, respectively. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A3: Impact of exposure to robots on employment (excl. initial import reliance)

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in employment-to-population ratio, 2000–2015					
Exposure to *domestic* robots	1.462*	1.266	2.027**	4.609**	3.163	3.916**
	(0.826)	(0.875)	(0.815)	(1.919)	(2.078)	(1.750)
Exposure to *foreign* robots excl. import reliance	-19.353***	-18.056***	-22.963***	-36.842***	-28.145**	-31.016***
	(3.959)	(4.254)	(4.546)	(11.186)	(12.213)	(10.080)
R^2	0.478	0.504	0.520	0.528	0.600	0.413
Region dummies	✓	✓	✓	✓	✓	✓
CZ demographics		✓	✓	✓	✓	✓
Broad industry shares and import reliance of US			✓	✓	✓	✓
Computerization and Chinese trade competition				✓	✓	✓
Initial conditions					✓	
Remove top 1%						✓
Observations	1,805	1,805	1,805	1,805	1,805	1,788

Notes: All specifications are identical to Panel B of Table 2, except that the exposure to foreign robots now does not include the initial reliance of US industries on Mexican imports. For ease of comparison, the values are normalized to have the same mean as the original variable.

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